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ORIGINAL ARTICLE

Institutional pressures on setting up big data analytics capability

Luciana Klein[1]
https://orcid.org/0000-0001-6815-1831
Email: lucianaklein@ufpr.br

Ana Paula Sano Guilhem[1]
https://orcid.org/0000-0002-3892-9515
Email: anapolletti@hotmail.com

Henrique Adriano de Sousa[1,2]
https://orcid.org/0000-0002-7740-3946
Email: henriquesousa@prof.unipar.br

Everton Lucio Soares de Oliveira[3]
https://orcid.org/0000-0003-3586-651X
Email: evertonadmcontabeis@outlook.com

[1] Universidade Federal do Paraná, Setor de Ciências Sociais Aplicadas, Departamento de Ciências Contábeis, Curitiba, PR, Brazil
[2] Universidade Paranaense, Departamento de Administração, Cascavel, PR, Brazil
[3] Independent researcher currently unaffiliated, São Manoel do Paraná, PR, Brazil

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ABSTRACT

This article aims to analyze the setting up of tangible resources and human big data skills, in the face of institutional pressures, in the big data analytics capability in Brazilian companies. Innovation influences the environment in which companies are inserted, increasing uncertainties, resulting in behavioral changes of social players. In response to individual efforts to rationally deal with uncertainties and constraints, organizational homogenization emerges. However, the institutional pressures that influence the setting up of specific resources are still not fully understood in the literature. The replication of the study by Dubey (2019b) is considered, seeing big data technology as an innovation that has caused changes in the social context, thus we seek to grasp the setting up of organizational big data resources in Brazilian companies to build BDA capability, due to institutional pressures. The study makes it possible to see how institutional pressures set up BDA capability, thus being able to provide means to investment allocation decisions in data technology or improve technical management skills in the business intelligence team. The study brought to light the environmental response, resulting from the technological innovation of big data, in Brazilian companies. This demonstrates that organizations adhering to big data technology select their resources in the face of various pressures, in order to build big data analytics capability. This research has a descriptive and quantitative nature, and its operationalization took place through a survey. The research population consists of Brazilian companies that use technology with a large volume of structured and/or unstructured data, to generate results and insights, which support decision making. The survey participants were employees of Brazilian companies that have positions related to building big data analytics capability, located through the *LinkedIn* platform. 136 valid responses were obtained. To test the hypotheses, the Structural Equation Modeling technique was used by means of the software *Smartspls* v. 3.2.3. This study contributes by bringing an understanding of organizational behavior in the face of institutional pressures (coercive, normative, and mimetic) when selecting tangible resources and human big data skills to build BDA capability, using Resource-Based Theory. It is observed that the setting up of BDA capability is influenced by tangible resources and human skills. Tangible resources are selected due to formal pressures, competitive conditions, and by imitating existing standards in the market. Meanwhile, the required human skills are impacted, through legitimation and professional networks of decision makers.

Keywords: institutional pressures, big data analysis, Resource-Based Theory, big data organizational resources, Industry 4.0.

Correspondence address

Luciana Klein
Universidade Federal do Paraná, Setor de Ciências Sociais Aplicadas, Departamento de Ciências Contábeis
Avenida Prefeito Lothário Meissner, 632 – CEP 80210-170
Jardim Botânico – Curitiba – PR – Brazil

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1. INTRODUCTION

The technological progress triggered by Industry 4.0 impacts organizations exponentially, thus, to maintaining market competitiveness, they seek to implement strategies to adhere to technological innovations in order to obtain financial performance and market positioning. However, building organizational capability is needed and not just implementing new technologies, which is obtained by combining tangible and intangible resources and human skills, according to the Resource-Based Theory (Barney, 1991; Barney et al., 2011; Grant, 1991; Mikalef et al., 2018; Yu et al., 2018). However, the environment in which organizations are inserted is uncertain, which impacts on competitiveness.

DiMaggio and Powell (1983) point out that external factors increase uncertainties and constraints to the organization, thus, the rationality of organizational players to deal with pressures leads the organizational field to homogenization, and this phenomenon is named *institutional isomorphism*. Isomorphism takes place through institutional pressures in three aspects: (i) coercive, which occurs through political influences and legitimacy issues; (ii) mimetic, resulting in standardization due to uncertainties; and (iii) normative, which is related to norms associated with professionalization (DiMaggio & Powell, 1983). Thus, in response to individual efforts to deal with uncertainties and constraints in a rational way, the homogenization of culture, structure, and results of organizations emerges (DiMaggio & Powell, 1983).

Despite the rational decisions of organizational players restricting skills for future changes, there are those who seek improvements by adopting organizational innovations (DiMaggio & Powell, 1983), mainly in aspects that require building organizational capabilities (Oliver, 1997). A technology that has stood out, within Industry 4.0, is big data, seen as a technological disruption in business and academic ecosystems since the rise of Internet and the digital economy. Big data is defined by the large volume of data from various sources, whether structured or not (Arunachalam et al., 2018; Brinch et al., 2018; Félix et al., 2018; Mikalef et al., 2019). However, this technology alone does not provide benefits, it is necessary to build Big Data Analytics (BDA) capability, defined by the strategic combination of tangible and intangible resources and human big data skills (Gupta & George, 2016).

BDA capability has been related to several benefits, such as decision-making embodied through a large volume of information, greater bargaining power vis-à-vis suppliers and customers (Falsarella & Jannuzzi, 2020), supply chain improvement, demand planning improvement, improvement in sales and operations planning capability, and financial performance improvement (Cabrera-Sánchez & Villarejo-Ramos, 2019; Mikalef et al., 2018; Queiroz & Pereira, 2019; Schoenherr & Speier-Pero, 2015; Zhang et al., 2017).

Despite the scarcity of literature results in a limited understanding of the impact on management controls, Vitale et al. (2020) found that big data has various implications in the formal and informal dimensions of the management control system of a small company in Germany. In the formal dimension, big data reinforces the budgeting process, but does not change the formal artifacts, while the informal dimension is strengthened, rationalized, and formalized. In turn, Bergmann et al. (2020) found that the sophistication of data infrastructure is positively associated with the use of business analytics in the budgeting process. Also, the authors concluded that the more a company emphasizes the planning function, the more business analytics is used. In Brazil, it is possible to highlight the importance of this study when relating big data derivations with management systems such as Business Intelligence (BI) (Reginato & Nascimento, 2007). In the same sense, the application of big data systems linked to accounting and management tools such as the Balanced Scorecard becomes apparent (Galas & Ponte, 2006).

However, the adoption of big data resources does not always occur strategically, in this sense, relevant institutional issues are raised to explain the origin and dissemination of technologies related to Industry 4.0. Fogaça et al. (2022) argue that: (i) different and specific ways of justification are emphasized by various types of organizations (such as companies, unions, universities, and governments) when adopting Industry 4.0; (ii) it is a social movement that has the German government as one of its major institutional entrepreneurs; (iii) it will acquire different meanings as it spreads among countries with different institutional characteristics.

From an institutional perspective, companies seek to respond to pressures from various stakeholders and analyze the behavior of other players in the organizational field. In this sense, institutional pressures (coercive, normative, and mimetic) force the adoption of big data technology, through the setting up of key resources, tangible resources, and human skills. In the tangible aspect, they include technology, primary resources, and data, while in the human aspect it refers to the analytical and technical data capability (Gupta & George, 2016).

Interactions between institutional pressures, human skills, and tangible resources were observed in Dubey et al. (2019b), whose evidence pointed out that pressures have significant effects on the selection of tangible resources in manufacturing companies in India, directly affecting the allocation of internal resources and the adoption of BDA. However, the authors point out that coercive pressures, in the context analyzed, do not have a significant effect on human skills. Bag et al. (2021), when analyzing automotive companies operating in South Africa, found a significant relationship between institutional pressures and the adoption of tangible resources, with emphasis on coercive pressures on tangible resources. The authors also state that the South African government, through the Black Economic Empowerment (BEE) certificate and the Skills Development Act, requests companies to update data programming and analysis, so that there is qualification of human resources for economy growth. Thus, institutional pressures are also associated with workforce skills.

Thus, institutional pressures guide a company to operate within social boundaries and most countries have shaped their individual digital strategies to carry out digital programs within these social boundaries (Gerrikagoitia et al., 2019). In Brazil, external pressure from government agencies, such as the National Innovation System (Sistema Nacional de Inovação [SNI]), the Ministry of Science, Technology, and Innovation and Communications (Ministério da Ciência, Tecnologia e Inovações e Comunicações [MCTIC]), and the Ministry of Development of Industry and Foreign Trade and Services (Ministério do Desenvolvimento da Indústria e Comércio Exterior e Serviços [MDIC]) serve as massive measures for technological insertion, driving companies to align and operate within the Brazilian digital strategy (Silva, 2019). Customer pressures also force suppliers to adopt digital technologies to set up their resources and capabilities (Cabrera-Sánchez & Villarejo-Ramos, 2019; Félix et al., 2018).

It is argued that institutional pressures influence the setting up of key resources to build BDA capability, which can help with competitive and financial performance (Mikalef et al., 2018; Yu et al., 2018). Therefore, Dubey (2019b) was replicated in order to indicate how institutional pressures lead to building BDA capabilities. In Brazil, digital transformation has been driven mainly by government agencies, thus this study aims to analyze the setting up of tangible resources and human big data skills, in the face of institutional pressures, in BDA capability in the context of Brazilian companies.

It worth grasping how social structures influence and change processes and the organizational structure, in order to visualize business opportunities (Francisco et.al., 2020) and the possible impacts at the companies' managerial level. That said, this study makes it possible to see how institutional pressures set up BDA capability, thus being able to provide means to decisions on the allocation of investment in data technology or improvement of technical and managerial skills of the business intelligence team. Thus, the study has the potential to highlight the importance of human skills in building competitive advantage, as only investments aimed at collecting large volumes of data and having access to sophisticated technologies do not guarantee a sustained competitive advantage.

Creating and maintaining a database for decision making, in the Industry 4.0 era, promises to change the roles of the CFO and controller, at the organizational and personal levels. Schäfer and Weber (2018), point out the need for CFOs and controllers to play an active role in addressing digital opportunities and the corresponding changes in business models and organizational strategies, which implies the creation and adaptation of new performance indicators, blending traditional and digital business models. Creating and maintaining a database for decision making has always been the core responsibility of the finance department, however, this role is increasingly challenged by data scientists and other IT functions (Möller et al., 2020; Schäfer & Brueckner, 2019). At a personal level, the need to build expertise in big data and analytics becomes latent. Thus, grasping the role of human skills and tangible resources in BDA capability can sustain changes at the organizational and personal levels of Brazilian companies.

2. INSTITUTIONAL PRESSURES, RESOURCES, SKILLS AND BIG DATA ANALYTICS CAPABILITY

Organizational behavior is subject to pressures exerted by institutions, such as social and regulatory forces, direct control relationships and organizational transactions, derived from the environment (DiMaggio & Powell, 1983; Guarido & Costa, 2012; Scott, 1994, 2008). From an institutional perspective, new organizational practices are guided and shaped by external institutions and interactions between organizations (DiMaggio

& Powell, 1983; Guarido & Costa, 2012; Williams & Spielmann, 2019). Adherence to new technologies and behavioral changes in the organization happen in the institutional field through informal and formal pressures (DiMaggio & Powell, 1983; Oliver, 1991). These pressures refer to the Sociological Institutional Theory, which is based on three pillars: (i) cognitive, related to mimetic pressures, (ii) normative, related to normative pressures, and (iii) regulatory, related to coercive pressures (Fonseca, 2003). Due to these pressures, organizations become homogeneous, a phenomenon known as *institutional isomorphism*. Isomorphism may be coercive, mimetic, and normative (DiMaggio & Powell, 1983).

Coercive isomorphism derives from informal and formal pressures and cultural expectations suffered by organizations dependent on others. These pressures are explained through persuasion and coercion, as well as government orders (DiMaggio & Powell, 1983). Mimetic isomorphism arising from symbolic uncertainty and when there are ambiguous goals. One response to this uncertainty is to follow a model already used by other organizations, encouraging imitation. Normative isomorphism stems from professionalization, consisting of two aspects, the first being legitimation of university experts and support for formal education, and the second the constitution of professional networks collaborating for a rapid dissemination of models, such as knowledge sharing between professionals and consulting firms (Adjei et al., 2021; DiMaggio & Powell, 1983; Irwin et al., 2021).

Isomorphism should be regarded as added to competitiveness (Hannan & Freeman, 1977), which occurs through institutional pressures and the latter have a positive relationship with regard to selection of resources in organizations (Dubey et al., 2019b; Meyer & Rowan, 1977). External forces generate the need for adaptation in organizations. This adaptability is observed and required in the context of the fourth Industrial Revolution, also known as Industry 4.0, which includes various technologies such as the *internet of things*, robotics, and big data, making organizations seek innovation and technological adoption motivated by international and national trends and competitive advantage (Sakurai & Zuchi, 2018).

Institutional pressures force the adoption of Industry 4.0 technologies, through the setting up of key resources, mainly related to tangible resources and human skills (Chahal et al., 2020). Resource-Based Theory (RBT) argues that organizational resources and the development of capabilities strategically can provide competitive advantage (Barney, 1991, 2001; Chahal et al., 2020; Cruz & Haugan, 2019; Grant, 1991). As an example of resources, tangible assets or inputs that an organization owns, controls or has access to on a semi-permanent basis may be cited (Helfat & Peteraf, 2003). These resources are used by companies through skills, which are made up of physical and human aspects needed for the company to serve its customers.

Under the RBT approach, resources are the basic units of analysis, which can be physical capital (equipment, technology, and raw materials), human capital (employee insights, experience, training, intelligence, judgment, and relationships), and organizational capital (formal and informal planning, control systems, and reporting structure), with a heterogeneous nature, due to the various strategies adopted by organizations (Barney, 1991; Grant, 1991; Oliver, 1997). When applying the RBT concepts, Gupta and George (2016) classify big data organizational resources as shown in Figure 1.

Tangible Resource	Data (internal, external and merging of both); Technology; Primary resources (time and investment).
Human Resource	Management skills (analytical acumen); Technical skills (education and training related to specific big data skills).
Intangible Resource	Data-driven culture (decisions based on data rather than intuition); Organizational learning intensity (ability to explore, store, share and apply knowledge).

Figure 1 *Big data organizational resources*
Source: *Adapted from Gupta and George (2016).*

Gupta and George (2016) proposed the idea of BDA capability built through the RBT approach, which deals with the relationship between resources and capabilities, with resources being the source of organizational capability. The result of combining resources with teamwork constitutes organizational capability, which is specific to each company (Grant, 1991; Makadok, 2001).

Thus, with a focus on big data technology, organizations build BDA capability by combining resources directed towards this technology. Organizations are influenced by the context in which they are inserted, due to institutional pressures (Grant, 1991; Gupta & George, 2016; Vidgen et al., 2017). These pressures directly impact access to resources, as these are related to improving information analysis and quality, which reflect company performance (Dubey et al., 2016, 2019b).

Coercive pressure comes from other organizations, sociocultural expectations, external bodies that have authority to interfere with organizational behavior and structure, through company policies, laws, and regulations (DiMaggio & Powell, 1983). Examples are business associations, government agencies, International Organization for Standardization (ISO) standards, and the General Data Protection Law (Lei Geral de Proteção de Dados [LGPD]). Pressure can be exerted on tangible resources with government interventions through regulatory standards regarding data, national policies, and funding to foster technologies (Bag et al., 2021; Dubey et al., 2019b). Human skills can be seen in meeting the expectations of suppliers, stakeholders and customers (Dubey et al., 2015, 2016; Liang et al., 2007). Thus, we have the following hypotheses:

> ***H_{1a}:*** *Coercive pressure has a positive relationship with tangible big data resources.*

> ***H_{1b}:*** *Coercive pressure has a positive relationship with human big data skills.*

Normative pressure stems from professionalization, based on the specialization process, establishing norms and values in the organization in order to achieve goals established with clients and other professionals (Dubey et al., 2015, 2016; Liang et al., 2007). Such pressure on tangible resources puts pressure on the organization's development, as technological inadequacy can lead to intermittent negotiations by suppliers and customers (Bag et al., 2021). The influence of normative pressure on human skills may occur due to regular training and workshops, which help professionals to adapt to the institution (Dubey et al., 2015). Therefore, the following hypotheses are proposed:

> ***H_{2a}:*** *Normative pressure has a positive relationship with tangible big data resources.*

> ***H_{2b}:*** *Normative pressure has a positive relationship with human big data skills.*

Mimetic pressures on tangible resources are related to the benefits and competitive advantage observed in other companies (Bag et al., 2021). In human skills, organizational management and relationship with suppliers are in line with existing practices in similar organizations (Dubey et al., 2015, 2016; Liang et al., 2007). Thus, we have these hypotheses:

> ***H_{3a}:*** *Mimetic Pressure has a positive relationship with tangible big data resources.*

> ***H_{3b}:*** *Mimetic Pressure has a positive relationship with human big data skills.*

Company value can be increased through disruptive resources, however, there is a need to align strategies to adapt big data deployment, because through these strategies the proper technique and algorithm speed will be selected (Gupta & George, 2016; Loshin, 2013). Interconnection of resources is part of the building of BDA capability proposed by Gupta and George (2016) as the capability for organizational development based on the deployment, assembly, and interconnection of resources. In this way, for the results to be observed by the organization, infrastructure is key to carry out data processing and analysis with agility, obtained through tangible resources that provide the basis for a large volume of data from various sources (Gunasekaran et al., 2017; Gupta & George, 2016; Srinivasan & Swink, 2018). This stems from the combination of big data technology with human skills to generate BDA capability, which enables predictive analytics, descriptive analytics that include trending information, and prescriptive analytics (Duan et al., 2020; Srinivasan & Swink, 2018).

These types of analyses help in restricting informational asymmetry, improving company performance, analyzing performance, making decisions, which contribute to improving strategic control, management information quality, new investment selection, efficient budget allocation, enabling continuous improvement (Akter et al., 2016; Dubey et al., 2019a; Madeira Pontes et al., 2021; Medeiros et al., 2021; Srinivasan & Swink, 2018). Thus, we have the following hypothesis:

> ***H_4:*** *Tangible big data resources have a positive relationship with BDA capability.*

Human BDA skills are dichotomous, being managerial the skills that demand deeper knowledge to carry out strategic planning and technical those skills that involve data extracting and cleaning and grasping programming paradigms. These skills encompass knowledge, judgment, adequate experience, correct education, and training for the environment that uses BDA. Skills are key to understanding the business, customers, suppliers, and effectively coordinating internal departments (Gupta & George, 2016). Human knowledge drives which sector and which information generated will be most appropriate and can be applied strategically, operationally, or tactically (Pauleen & Wang, 2017). Based on this knowledge, data analysts carry out checks and provide the organization with useful insights (Azeem et al., 2022). Therefore, the following hypothesis is formulated:

> ***H_5**: Human big data skills have a positive relationship with BDA capability.*

Thus, to grasp the setting up of BDA capability, it is necessary to consider the institutional context, as institutional pressures influence the setting up of the organization's internal resources, causing tangible resources and human skills to be selected in various ways in response to the environment, providing better explanation in the decision of the BDA adoption process (Dubey et al., 2019b). Based on the stated hypotheses, Figure 2 presents the theoretical model, highlighting the relationship between institutional pressures, organizational resources, and BDA capability. In order to analyze the behavior of tangible resources and big data human skills, in the face of institutional pressures, in the building of BDA capability.

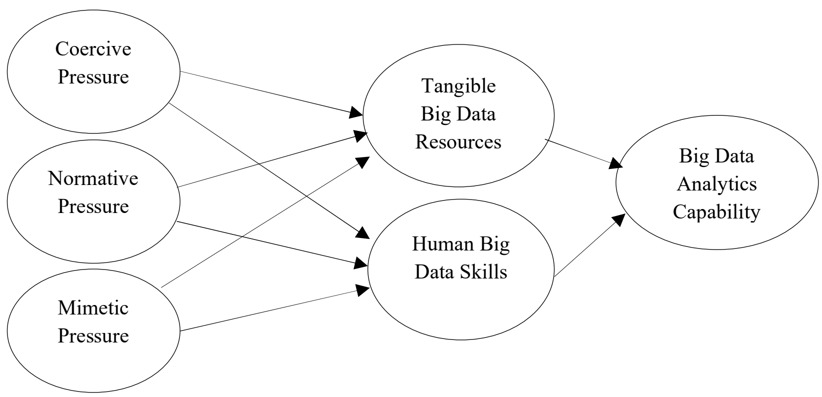

Figure 2 *Theoretical research model*
Source: *Prepared by the authors.*

The model does not consider the intangible resource, identified by Gupta and George (2016), big data culture and organizational learning, as the transition to an organizational culture of data-driven decision-making is complex and not always fast, as well as intensifying organizational learning is a gradual process. In Brazil, also, the main barriers faced by organizations that have implemented big data are related to establishing innovative processes, the experimentation culture, and organizational structure reviews (Félix et al., 2018).

3. RESEARCH METHOD AND PROCEDURES

3.1 Sample Selection and Data Collection

The study population consists of Brazilian companies that use big data technology to analyze large amounts of (structured and unstructured) data to generate major results and insights that help decision making (Gupta & George, 2016). To access the target population and build the sample, *LinkedIn* platform users were tracked using the terms "*big data*", "*data analytics*" and "*data scientist*"; these individuals are employees of Brazilian companies with positions related to building BDA capacity. Thus, the sample consists of respondents who have positions such as: Data Scientist, Manufacturing Excellence, Infrastructure Analyst, Data Analyst, Manufacturing IT, Market Intelligence Analyst, Business Intelligence Analyst, Continuous Improvement Manager, Business Intelligence, Head of Manufacturing Excellence, and Quality Manager and Controller.

Then, 450 invitations were sent to connect via *LinkedIn* with employees of these companies who had positions related to management and BDA, and 204 accepted to join the network. Those who accepted the invitation were sent a link to the research instrument via *Google Forms*. For greater adherence, when requested, the research instrument was sent via e-mail. The data collection period was from May 6 to June 1, 2021.

The estimation of the necessary sample was performed using the software *G*PowerWin* 3.1.9.4 (Faul et al., 2009), following the recommendations of Cohen (1988) and Hair et al. (2014), when using the test power 0.80, median f2 = 0.15, the minimum sample defined for the study was 77 cases, considering the construct with the highest number of links (Figure 2). A total of 154 responses were obtained, but 17 questionnaires in which the question referring to the use of big data was not answered positively were excluded. Thus, the non-random sample consisted of 136 appropriate responses. Also, ethical procedures were guaranteed through respondent anonymity, confidentiality of obtained data, as well as analysis and dissemination of results.

3.2 Research Constructs and Measurement of Variables

The research has three main constructs, namely institutional pressures, which involve coercive, normative, and mimetic pressures (DiMaggio & Powell, 1983), big data organizational resources, characterized by tangible resources and human skills (Gupta & George, 2016), and BDA capability (Srinivasan & Swink 2018). The constructs were measured using multiple items and respondents' agreement level using a Likert scale, ranging from (1) I totally disagree to (5) I totally agree, as shown in Figure 3.

Constructs	Operational definition	Scale	Authors
Coercive Pressure	Coercive pressure comprises: (i) data protection laws; (ii) rules and regulations; (iii) social pressure.	5 indicators 5-point Likert scale	Liang et al. (2007) and Dubey et al. (2019b)
Normative Pressure	Normative pressure consists of: (i) promotion of technological extension through associations; (ii) the company's suppliers and customers adhere to big data technology.	5 indicators 5-point Likert scale	Dubey et al. (2019b)
Mimetic Pressure	Mimetic pressure is observed through the adherence of competitors to big data and the benefits obtained and perceived as favorable.	5 indicators 5-point Likert scale	Liang et al. (2007) and Dubey et al. (2019b)
Tangible Big Data Resources	Tangible resources are pointed out through the use of: (i) a large volume of structured or unstructured data; (ii) technologies to support data; (iii) integration of internal and external data to the company.	5 indicators 5-point Likert scale	Dubey et al. (2019b)
Human Big Data Skills	Human skills are observed through recruitment, selection, and training with a focus on developing data-driven decision-making.	5 indicators 5-point Likert scale	Dubey et al. (2019b)
Big Data Analytics Capability	BDA capability was captured through the ease of integration of technological resources (dashboards) and analytical techniques for establishing routines based on data.	4 indicators 5-point Likert scale	Dubey et al. (2019b)

Figure 3 *Constructs, operational definition, and scale*
Source: *Prepared by the authors.*

To capture institutional pressures, 15 assertions were used, 5 for each institutional, coercive, normative, and mimetic pressure adapted from Liang et al. (2007) and Dubey et al. (2019b). Tangible resources and human big data skills also had 5 assertions each, derived from Dubey et al. (2019b). To measure BDA capability, 4 assertions were used having Srinivasan and Swink (2018) as a basis. As the assertions have come from foreign instruments, the process of translation and reverse translation was applied (Pedroso et al., 2004), and subsequently the pre-test was carried out, with professionals in the area and doctoral students, in order to adapt and validate the questionnaire to the Brazilian reality, culture, and legislation.

In addition to the 29 assertions (Appendix A) that seek to measure the research constructs, the research instrument has used a control question, in order to select companies that use a large volume of structured and/or unstructured data.

3.3 Data Analysis Procedures

The hypotheses were tested using the Structural Equation Modeling technique through the software *Smartspls* v. 3.2.3. As data collection resorted to only one method, the recommendations of Podsakoff et al. (2003) have been observed, to avoid common method bias. To do so, first, the assertions in the questionnaire were randomly organized, in order to avoid possible association between the constructs by respondents. Then, the questionnaire was sent directly to respondents. After collection, the Harman single-factor test was performed, in which a high amount of variance comprised by a single factor may indicate common method bias (Podsakoff et al., 2003); the test is performed through exploratory factor analysis including all variables, independent and dependent, and it is expected that only one factor does not correspond to more than 50% of the variance. In this sense, it is observed that a single factor represented 24.24% of the variance, suggesting that there are no issues with regard to common method bias.

4. DATA ANALYSIS

4.1 Sample Characteristics

Each response received is equivalent to one company surveyed. Thus, in relation to the business characteristics, according to Table 1, companies in which respondents perform their professional activities, 93.43% have more than 99 employees, showing that the sample of this research mostly comprises large companies.

Table 1
Company characteristics

Company size	**Frequency**	**%**	**Sectors**	**Frequency**	**%**
Up to 9 employees	1	0.73	Technology	12	8.76
From 10 to 49 employees	4	2.92	Automotive	13	9.49
From 50 to 99 employees	4	2.92	Cosmetics	13	9.49
More than 99 employees	128	93.43	Mining	6	4.38
Sectors	Frequency	%	Pharmaceutical and hospital care	6	4.38
Food	38	27.74	Construction	6	4.38
Agribusiness	19	13.87	Clothing	3	2.19
Others	18	13.14	Services	3	2.19

Source: *Prepared by the authors.*

When analyzing the activity sector, it was identified that there were 3 large groups with greater frequency. The first was food, representing 27.74% of the sectors, the second was agribusiness, with 13.87%, and the third was identified as others, with 13.14%, comprising the following sectors: aeronautics, transport, research, environment, quality, supplies, paper and cellulose, goods and consumption, home appliances, and electrical engineering.

4.2 Assessing the Measurement Model

Assessing the reflective measurement model includes evaluating the reliability of indicators that make up the construct, composite reliability, convergent validity (average variance extracted – AVE), and discriminant validity. First, the reliability of the indicators that make up the research instrument is assessed, according to Hair et al. (2021) loads above 0.708 indicate that the construct explains more than 50% of indicator variance. In social research, weaker loads are usual, especially in exploratory instruments, a situation observed in this research. In this sense, the authors advise assessing the effects of removing indicators, which is only recommended when it increases composite reliability or convergent validity. Thus, 8 indicators were excluded, 3 assertions referring to the construct coercive pressures, 2 assertions about normative pressures, 2 assertions about the construct tangible resources, and 1 assertion of the construct human skills (Table 2).

Excluded items did not affect construct content validity. Furthermore, according to Table 2, all constructs, after exclusions, showed values above the indicated for composite reliability (0.70) and AVE (0.50) (Hair et al., 2021).

Table 2
Model suitability indexes

	Indicator loads	Compound Reliability	Convergent Validity (AVE)	Indicator loads	Compound Reliability	Convergent Validity (AVE)
		Before	Before		After	After
Coercive Pressure	q1 = 0.498	0.465	0.289	–	0.869	0.625
	q2 = 0.697			q2 = 0.842		
	q3 = 0.806			q3 = 0.789		
	q4 = 0.008			–		
	q5 = 0.249			–		
Normative Pressure	q6 = 0.748	0.806	0.457	q6 = 0.801	0.885	0.661
	q7 = 0.647			–		
	q8 = 0.521			–		
	q9 = 0.702			q9 = 0.630		
	q10 = 0.737			q10 = 0.834		
Mimetic Pressure	q11 = 0.756	0.94	0.758	q11 = 0.765	0.799	0.666
	q12 = 0.891			q12 = 0.896		
	q13 = 0.920			q13 = 0.919		
	q14 = 0.925			q14 = 0.921		
	q15 = 0.851			q15 = 0.842		
Tangible Resources	q16 = 0.578	0.773	0.405	–	0.94	0.758
	q17 = 0.637			–		
	q18 = 0.628			q18 = 0.677		
	q19 = 0.652			q19 = 0.697		
	q20 = 0.683			q20 = 0.815		
Human Skills	q21 = 0.595	0.878	0.595	–	0.802	0.578
	q22 = 0.707			q22 = 0.695		
	q23 = 0.894			q23 = 0.898		
	q24 = 0.844			q24 = 0.854		
	q25 = 0.781			q25 = 0.791		
BDA Capability	q26 = 0.798	0.869	0.625	q26 = 0.796	0.775	0.536
	q27 = 0.853			q27 = 0.857		
	q28 = 0.794			q28 = 0.792		
	q29 = 0.711			q29 = 0.710		

AVE = average variance extracted.
Source: *Prepared by the authors.*

It can be stated that, after adapting the measurement model, the items of the research instrument do not show redundancy or undesirable response patterns, and also that the constructs explain 53.6% (BDA Capability) or more of indicator variance in the construct. Next, the discriminant validity of constructs is estimated to assess the independence between them, i.e. whether there is an empirical distinction between the constructs. It was identified, as shown in Table 3 (shaded), that there is discriminant validity. As an additional discriminant analysis, the heterotrait–monotrait ratio (HTMT) 0.85 is evaluated. Henseler et al. (2015) propose a threshold value of 0.85 for structural models with conceptually more distinct constructs, thus confirming the empirical distinction between constructs.

Table 3
Discriminant validity

	BDA C		Hum. S.		Coerc. P.		Mim. P.		Norm. P.		Tang. R.
BDA C	0.791*										
Hum. S.	0.602	0.719**	0.813*								
Coerc. P.	0.086	0.233	0.046	0.135**	0.816*						
Mim. P.	0.338	0.390	0.317	0.352	0.212	0.313**	0.871*				
Norm. P.	0.276	0.393	0.375	0.497	0.378	0.669	0.532	0.689**	0.760*		
Tang. R.	0.377	0.574	0.279	0.415	0.407	0.766	0.383	0.519	0.369	0.613**	0.732*

** Fornell-Larcker Criterion; ** Heterotrait–monotrait ratio (HTMT).*
Source: *Prepared by the authors.*

Thus, it may be stated that the measurement model allows for a satisfactory estimation of the relationships between institutional pressures (coercive, mimetic, and normative), organizational resources (tangible resources and human skills), and BDA capability.

4.3 Assessing the Structural Model and Hypothesis Testing

The next step is to evaluate the structural model, for which Pearson's Coefficients of Determination (R^2), Variance Inflation Factor (VIF), and Predictive Relevance (Q^2) are assessed. R^2 values indicate model quality, pointing out the variance percentage of an endogenous variable explained by the structural model (Ringle et al., 2014). According to Cohen (1988), the effects in social sciences may be classified as follows: $R^2 = 2\%$ as small effect; $R^2 = 13\%$ as medium effect; and $R^2 = 26\%$ as large effect.

It is observed in Table 4 that the smallest R^2 among the constructs was 17.1% for "Human skills", results considered median in the literature. On the other hand, the R^2 for "Tangible resources" (26.6%) and "BDA capability" (41%) are considered large effects. According to Chin (1998), when the values for predictive relevance (Q^2) are greater than zero in the endogenous latent variables, there is predictive relevance, thus, it is observed that the structural model does not have any value below zero, thus providing predictive relevance. The standard metric for assessing collinearity is the variance inflation factor (VIF), when VIF values of 5 or greater indicate collinearity issues (Hair et al., 2021).

Table 4
Structural model adjustments

	R^2	Q^2	VIF		
			BDA Capability	Human Skills	Tangible Resources
BDA Capability	0.410	0.242			
Human Skills	0.171	0.101	1.085		
Tangible Resources	0.266	0.112	1.085		
Coercive Pressure				1.167	1.167
Mimetic Pressure				1.395	1.395
Normative Pressure				1.555	1.555

Source: *Prepared by the authors.*

Next, hypotheses were tested for each path diagram of the structural model (Table 5).

Table 5
Hypothesis Testing – Direct and indirect effects

Structural relationships	Direct	Indirect	T test	P value
Coercive Pressure -> Tangible Resources	0.308		3.723	0.000***
Coercive Pressure -> Human Skills	-0.114		0.826	0.409
Normative Pressure -> Tangible Resources	0.117		1.081	0.280
Normative Pressure -> Human Skills	0.331		3.126	0.002**
Mimetic Pressure -> Tangible Resources	0.255		2.855	0.004**
Mimetic Pressure -> Human Skills	0.165		1.531	0.126
Human Skills -> BDA Capability	0.539		6.882	0.000***
Tangible Resources -> BDA Capability	0.227		2.751	0.006**
Coercive Pressure -> BDA Capability		0.009	0.098	0.922
Normative Pressure -> BDA Capability		0.205	3.315	0.001***
Mimetic Pressure -> BDA Capability		0.147	2.192	0.028**

*P < 0.001*** P < 0.05**.*
Source: *Prepared by the authors.*

The results in Table 5 show that human skills are impacted by normative pressure (0.331, $p < 0.001$), while tangible resources suffer coercive (0.308, $p < 0.001$) and mimetic (0.255, $p < 0.005$) pressures. Regarding the building of BDA capability, the results indicate that both Tangible Resources (0.227, $p < 0.005$) and Human Skills (0.539, $p < 0.000$) are correlated, and Mimetic Pressure plays an indirect role in this correlation (0.147, $p < 0.005$), as well as Normative Pressure (0.205, $p < 0.001$).

Table 6
Hypothesis test - Specific indirect effect

Structural relationships	Specific	T test	P value
Coercive P.->Tangible Resources->BDA Capability	0.070	2.095	0.036**
Coercive P.->Human Skills->BDA Capability	-0.061	0.802	0.423
Normative P.->Tangible Resources->BDA Capability	0.026	1.014	0.311
Normative P.->Human Skills->BDA Capability	0.178	3.279	0.001***
Mimetic P.->Tangible Resources->BDA Capability	0.058	1.770	0.077
Mimetic P.->Human Skills->BDA Capability	0.089	1.371	0.170

*P < 0.001*** P < 0.05**.*
Source: *Prepared by the authors.*

Table 6 presents the specific indirect effect of the hypotheses H_1, H_2, H_3, H_4, and H_5. The results show that tangible resources mediate coercive pressure and BDA capability (0.070, $p < 0.005$), it is also observed the mediation of human skills with normative pressure and BDA capability (0.178, $p < 0.001$).

4.4 Analysis and Discussion of Hypotheses

The first hypothesis (H_{1a}) sought to verify whether coercive pressure has a positive correlation with tangible big data resources. The results were significant at $p < 0.001$, with coercive pressure associated with tangible big data resources, such as legislative forces and competitive conditions. This finding corroborates the results of Dubey et al. (2019b) and Bag et al. (2021), which demonstrated that tangible resources are influenced by data regularization norms, national policies, and funding for investment in technologies. In the Brazilian context, Silva (2019) points out that the SNI, MCTIC, and MDIC serve as technological influencers, boosting the Brazilian digital strategy.

H_{1b}, seeks to analyze whether coercive pressure has a positive relationship with human big data skills, the results were not significant. Therefore, this relationship is not observed in the sample, and it is necessary to investigate from different perspectives, as other results show significant relationships in different regulatory contexts, as in the case of Bag et al. (2021) in South Africa.

In this case, the South African government requests companies to update data programming and analysis, so that there is qualification of human resources and consequent economic growth.

H_{2a} seeks to verify whether normative pressure has a positive correlation with tangible big data resources, it is observed that they were not significant, i.e. from the perspective adopted in this study, it is not possible to state that there is legitimization of specific tangible resources by experts and/or formal education, or recommendation by professional networks that contribute to adherence of resources such as *Hadoop*, cloud computing or dashboards. This result may be based on the recent technological insertion of big data in Brazil, so it is possible that there is no consensus on which technologies are desired, which would allow a recommendation of which tangible big data resources should be adopted.

In turn, H_{2b}, which sought to analyze the relationship between big data human skills and normative pressure, had a significant consequence for p <0.05, it appears from this result that companies prioritize employees with technological insights and use human resources policy in order to capture human skills. In other words, the members of an organization define organizational behaviors through training and internal regulations to guide their professionals, resulting in legitimacy in line with the expectations of customers, suppliers, and other stakeholders (Liang et al., 2007; Dubey et al., 2015). In the Brazilian context, pressure to update human skills is internal (Félix et al., 2018) and, considering the view of the ecosystem (Francisco et al., 2020), the external environment changes through professional networks.

H_{3a} pointed out a positive association between mimetic pressures and tangible big data resources, being considered significant at $p < 0.05$. Therefore, it may be said that Brazilian companies are encouraged to select technological resources already accepted by companies in the organizational field, by their competitors. That is, technological resources are adopted by a company when benefits are observed in other organizations, mainly in environments with great environmental uncertainties (Bag et al., 2021; Dubey et al., 2015; Liang et al., 2007). However, there was no significance in hypothesis H_{3b}, which leads to the non-statement that companies observe and internalize the requirements of other organizations regarding the needs for technical and managerial skills of their employees.

In the fourth hypothesis (H_4) there is a significant positive relationship between tangible big data resources and BDA capability ($p < 0.05$), denoting that companies use cloud services and systems that support data processing, such as Hadoop, in addition to using different tools for data visualization and cloud computing. When these resources are applied to complementary tools, they help data visualization and processing, helping to build BDA capability, which adds value to the organization (Gunasekaran et al., 2017; Gupta & George, 2016).

In hypothesis five (H_5) the human big data skills and their positive relationship with BDA were analyzed, there is significance for $p < 0.001$, i.e. companies look for professionals with technical skills, in order to recruit new employees with experience in big data and predictive analytics, as well as building the right skills in BDA teams to make the job successful. In addition, they also employ managerial skills through managers who have a strategic business vision so that they can effectively integrate all departments and parts related to the company. Corroborating Bag et al. (2021), Dubey et al. (2019), and Gupta and George (2016), which reported the essentiality of training for the building of BDA skills, because stemming from knowledge, judgments, and experiences these skills serve to identify adequate strategies and useful insights for the effective coordination in the company (Azeem et al., 2022; Gupta & George, 2016; Pauleen & Wang, 2017).

Based on the RBT, it is observed that the companies participating in this study obtain BDA capability by investing more intensively in human big data skills, whereas in relation to tangible resources, less intensity is observed. Even though tangible big data resources are the basis for data processing, investment in professionals with technical and managerial skills is key, both being necessary to build BDA capability, as pointed out by Gupta and George (2016). Also analyzing the indirect effect in the relations between institutional pressures and BDA capabilities, it can be verified that normative and mimetic pressures have a positive relationship with BDA capability, with $p < 0.05$. Thus, it is demonstrated that professional networks and companies regarded as reference exert influence on the building of BDA capability with a view to reducing environmental uncertainties.

When analyzing specific indirect effects, it is observed that tangible resources mediate coercive pressure and BDA capability ($p < 0.05$), characterizing that the building of BDA capability is influenced by pressure from government agencies to adopt tangible big data resources, in order to boost the Brazilian digital strategy. It is also observed that human skill mediates the relationship between normative pressure and BDA capability, therefore, professional networks influence the human skills required for the building of BDA capability.

5. FINAL REMARKS

This research aimed to analyze the setting up of tangible resources and human big data skills, in the face of institutional pressures, in BDA capability in Brazilian companies. To do this, a survey was applied to Brazilian companies from various sectors that use big data technology, the sample consisted of 136 respondents. For data analysis, Structural Equation Modeling (SEM) was used.

Results suggest that companies in the sample adopt tangible big data resources as responses to coercive and mimetic pressures. From a practical viewpoint, this means that these companies are influenced by factors imposed by market competition, by the influence of the SNI, MCTIC, and MDIC that drive the Brazilian digital strategy, as already pointed out by Silva (2019), and also for observing that other companies that adhered to big data technology were successful. Furthermore, big data human skills are selected in response to normative pressure, with professionalization and specialization issues being geared towards building BDA capability.

Regarding resources and BDA capability, based on RBT, it is observed that the combination of tangible resources with human skills contribute to BDA capability, but human skills have greater significance when compared to tangible resources. Thus, it is possible to verify the importance of technical and managerial knowledge of data analytics, demonstrating that organizational capability is obtained by combining organizational resources, as pointed out by Grant (1991) and Makadok (2001). As for the relationships between institutional pressures and BDA capability, it is noticed that there is significance between mimetic and normative pressures. In this way, companies that observed the adoption models of big data technology, as well as those which joined professional networks, built a team capable of working with data efficiently.

In addition to the existence of an indirect relationship, the relationship between normative pressure and BDA capability is mediated by human skills, identifying that Brazilian companies set up BDA capability with technical and managerial skills, with skill needs influenced by the perception of experts and professionals who make up the professional network of decision makers. Also, it is observed that companies adopt tangible resources for the building of BDA capability due to pressure from government agencies, as well as competitive conditions.

The introduction of data analytics and automated forecasting technologies is already present, in view of this, identifying and properly applying appropriate techniques and drivers and a proper combination of human judgment and business acumen with extensive use of data and technology is key. In addition, new information routines can lead to a rather decentralized and self-service based decision-making and a reporting environment that can change the nature of control, as well as the role of controllers (Möller et al., 2020). In organizations, BDA capability allows new forms of intraorganizational cooperation through resources and abilities that can be shaped by environment pressures. Furthermore, BDA capability linked to institutional pressures can recursively influence the relationship between companies, suppliers, customers, and employees, leading to a new setting up of products, services, and organizational dynamics.

The accessibility sample is the main limitation of this article, in this sense, further studies could focus on specific sectors, in order to be able to conclude on potential differences between the various business sectors. In addition, due to environmental and information security concerns, studies aimed at sustainable development and information technology governance are recommended. It is also suggested to assess how digital technologies influence the roles that CFOs and controllers play in organizations. And it is also recommended to seek a greater understanding of the impact of Industry 4.0 technologies, in general, on the management control system.

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APPENDIX A

Research Instrument

Construct	Question	Questions	Derivations
Coercive Pressure (CP)	Q1	The General Data Protection Law (Lei Geral de Proteção de Dados [LGPD]) requires our company to use data securely.	Adapted from Liang et al. (2007) and from Dubey et al. (2019b)
	Q2	Our company uses a large amount of data due to the needs for competitive conditions.	
	Q3	Our company uses technological tools for data mining due to the requirements of competitive conditions.	
	Q4	Our company uses data and technological tools in order to meet the ISO requirements.	
	Q5	Our company uses data and technological tools under pressure from government agencies.	
Normative Pressure (NP)	Q6	Our company prioritizes technology-savvy employees to meet competitive conditions.	Adapted from Liang et al. (2007) and from Dubey et al. (2019b)
	Q7	Our suppliers use big data and predictive analytics for decision making.	
	Q8	Our customers use big data and predictive analytics for decision making.	
	Q9	The extent of promotion of big data and predictive analytics by industry associations influence our company to use big data and predictive analytics for decision making.	
	Q10	Our company uses a human resources policy in order to attract and retain experts in data management.	
Mimetic Pressure (MP)	Q11	Our competitors who have embraced big data and predictive analytics have benefited greatly.	Adapted from Liang et al. (2007) and from Dubey et al. (2019b)
	Q12	Our competitors who have embraced big data and predictive analytics are favorably perceived by others in the same industry.	
	Q13	Our competitors who have embraced big data and predictive analytics are favorably perceived for their suppliers.	
	Q14	Our competitors who have embraced big data and predictive analytics are favorably perceived by their customers.	
	Q15	Our competitors who have embraced big data and predictive analytics have staff training models that provide positive results.	
Tangible Big Data Resources (TR)	Q16	Our company integrates data from multiple sources into a single system.	Dubey et al. (2019b)
	Q17	Our company gathers external and internal data to facilitate the analysis of our business environment.	
	Q18	Our company uses parallel computing approaches (e.g. Hadoop) for data processing.	
	Q19	Our company uses different data visualization tools.	
	Q20	Our company exploits cloud-based services for data processing.	
Big Data Human Skills (HS)	Q21	Our company provides big data related training for our employees.	Dubey et al. (2019b)
	Q22	Our company recruits new employees who have experience in big data and predictive analytics.	
	Q23	Our big data analytics team has the right skills to get the job done successfully.	
	Q24	Our big data and predictive analytics managers have a strong understanding of the business.	
	Q25	Our big data and predictive analytics managers are able to effectively coordinate all intra departments, suppliers and customers.	
Big Data Analytics Capability (BDA)	Q26	Our company easily combines and integrates information from many data sources for use in decision making.	Adapted from Dubey et al. (2019b)
	Q27	Our company uses advanced analytical techniques (e.g. simulation, optimization, regression) to improve decision making.	
	Q28	Our company routinely uses data visualization techniques (e.g., dashboards) to help users or decision makers make sense of complex information.	
	Q29	Our dashboards give us the ability to break down information to help with root cause analysis and continuous improvement.	

Source: *Prepared by the authors.*